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Study on the Gas Content of Coal Seam based on the BP Neural Network

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Abstract

The prediction model for gas content in coal seam has been built based on the BP Neural Network to predict gas content accurately. And the model has been solved and forecasted by combining MATLAB programming with actual data. Moreover, the comparison analysis has been performed with the traditional prediction model based on multiple-regression. The results show that the non-linear gas content model related with basement buried depth and coal seam thickness etc could be established by utilizing the BP Neural Network. And its prediction accuracy and feasibility are better than the multiple-regression model. It is an ideal model for predicting gas content. It could provide some new ideas for the gas content prediction and the prevention and control for coal and gas outburst.

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Keywords: coal seam gas content; BP Neural Network; prediction; coal and gas outburst

1. Introduction

Ninety five percent Chinese coal mines are underground mining[1]. The coal seam occurrence condition is quite poor. The frequent disasters are related to coal and gas outburst. Therefore, the study on predicting the gas content in the coal seam would not only instruct to apply outburst prevention measures scientifically and reduce its related work amounts, but also guarantee the personal safety of the outburst layer owing to the continuous checking on the outburst risk of the outburst layer [2]. So the prediction of gas content is of great practical significance.

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In the late 1980s, the Neural Network as a new non-linear data processing technology has developed gradually. This method has strong non-linear function approximation ability, self-adaptive learning ability, tolerance capacity and parallel information processing power. It provides a new method for solving the modeling, predicting and control of uncertain nonlinear system and the data fusion approach [3,4]. With the popularization and development of the computer technology, the research and application of artificial neural network have made amazing progress, involving natural science, social science, applied science and comprehensive interdisciplinary science and other areas. Moreover, it has been widely used in intelligent control, pattern recognition, computer vision, adaptive filter and signal processing, nonlinear optimization, automatic target recognition, continuous speech recognition, sonar signal processing, the processing of knowledge, the sensing technology and robots, economic development forecast and even the weather forecast etc[5-7].

Considering the complexity, dynamics, nonlinearity and random uncertainty of the coal seam gas content system, we can utilize the Neural Network model to study the gas content. Based on the above analysis, in this study, we use the BP Neural Network to found the forecasting model for the coal seam gas content and provide reference for the gas content research on the spot to some extent.

2. Basic theory of BP Neural Network

2.1. BP neural network

Artificial Neural Network (ANN), which is also called as Neural Network (NN), is a subject derived from the signal transmission of the nervous system in the biology. It can be simply expressed as: Artificial Neural Network is an information processing system which aims to imitating the structure and function of the human brain [3].

Back Propagation Neural Networks (BPNN) was proposed by a scientific group of Rumelhart and McCelland in 1986. It is a multilayer feedforward networks using error reverse propagation algorithm and is one of the most widely used Neural Network models. Based on the error reverse propagation algorithm, BPNN has strong mapping ability and can solve many nonlinear problems.

The structure of the BPNN is shown as Fig.1, the node represents the neuron and the network consists of input layer nodes, hidden layer nodes and output layer nodes. The hidden layer can be single layer and also can be multilayer (The hidden layer in Fig.1 is single layer). Different layer nodes connect through arrows with weight. The essential idea is the learning process includes two sub-processes: forward propagating and backward propagating [8]. The forward propagating can be described as: the input signal spread from the input layer through hidden layer and then to the output layer, if the expected output is obtained, the learning algorithm is over, else turn to backward propagating. The backward propagating can be described as: calculating the error along the forward passage, and adjusting the weight and threshold between each layer nodes according to gradient descent method to reduce the error.

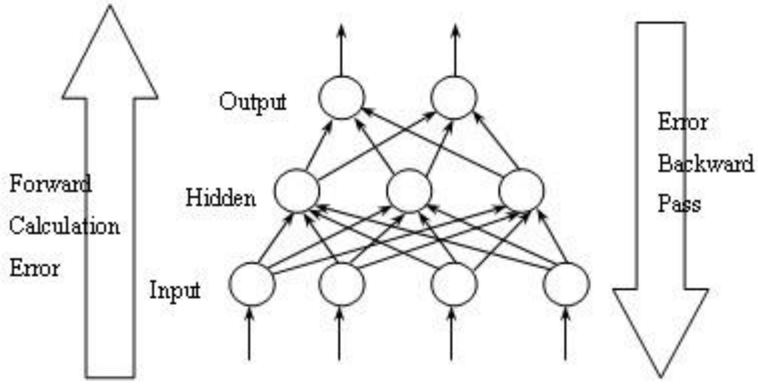

Fig.1 BP network module of one hidden-layer

2.2. BP algorithm

Set the input of BPNN as X, the number of the input layer neurons is n, the number of the hidden layer neurons is r_1, the relevant transfer function is f_1, the number of the output layer neurons is r_2, the relevant transfer function is f_2, the output is Y and the expectation is T.

1) The forward propagating of information

①The output of the ith neuron in the hidden layer:

$$y_{1i} = f_1\left(\sum_{j=1}^{n} w_{1ij}x_j + a_{1i}\right),\ j = 1,2,3,....,r_1 \tag{1}$$

②The output of the kth neuron in the output layer:

$$y_{2k} = f_2\left(\sum_{i=1}^{r_1} w_{2ki}y_{1i} + a_{2k}\right),\ i = 1,2,3,...,r_2 \tag{2}$$

③The error function is defined as:

$$E(W,A) = \frac{1}{2}\sum_{k=1}^{r_2}(t_k - y_{2k})^2 \tag{3}$$

2) Weight change calculating and the backward propagating of error

①Weight change of the output layer

The weight form the ith input to the kth output is:

$$\Delta w_{2ki} = -\eta\frac{\partial E}{\partial w_{2ki}} = -\eta\frac{\partial E}{\partial y_{2k}}\cdot\frac{\partial y_{2k}}{\partial w_{2ki}} = \eta(t_k - y_{2k})f_2' y_{1i} = \eta\delta_{ki}y_{1i} \tag{4}$$

Likewise:

$$\Delta a_{2k} = -\eta\frac{\partial E}{\partial a_{2ki}} = -\eta\frac{\partial E}{\partial y_{2k}}\cdot\frac{\partial y_{2k}}{\partial a_{2ki}} = \eta(t_k - y_{2k})f_2' = \eta\delta_{ki} \tag{5}$$

Where: $\delta_{ki} = (t_k - y_{2k}) f_2' = e_k f_2'$;; $e_k = t_k - y_{2k}$

②Weight change of the hidden layer

The weight form the j[th] input to the i[th] output is:

$$\Delta w_{1ij} = -\eta \frac{\partial E}{\partial w_{1ij}} = -\eta \frac{\partial E}{\partial y_{2k}} \cdot \frac{\partial y_{2k}}{\partial y_{1i}} \cdot \frac{\partial y_{1i}}{\partial w_{1ij}} = \eta \sum_{k=1}^{r_2} (t_k - y_{2k}) f_2' w_{2ki} f_1' x_j = \eta \delta_{ij} x_j \qquad (6)$$

Likewise:

$$\Delta a_{1i} = -\eta \frac{\partial E}{\partial a_{1ij}} = -\eta \frac{\partial E}{\partial y_{2k}} \cdot \frac{\partial y_{2k}}{\partial y_{1i}} \cdot \frac{\partial y_{1i}}{\partial a_{1ij}} = \eta \sum_{k=1}^{r_2} (t_k - y_{2k}) f_2' w_{2ki} f_1' = \eta \delta_{ij} \qquad (7)$$

Where: $\delta_{ij} = e_i f_1'$; $e_i = \sum_{k=1}^{r_2} \delta_{ki} w_{2ki}$.

3. Gas content forecast modeling based on BPNN

(1) The design of BPNN

Set the gas content as the dependent variable Y, take the geology factors such as the burial depth of the basement K_1, coal seam thickness K_2, the degree of metamorphism K_p etc. as the independent variables.

The relation between the mine content and the affect factors can be represent as:

$$Y = f(K_1,\ K_2, \ldots,\ K_p)$$

The gas content forecast model using three-layer BPNN can be shown as Fig.2. Take the number of the input nodes n=p, which is K_1, K_2, … , K_p; take the number of the output layer nodes l=1, which represents the gas content; take the number of the hidden layer nodes m=10.

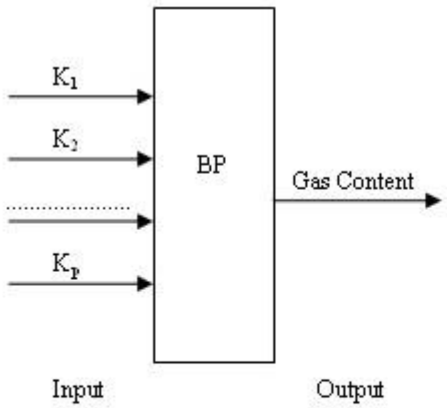

Fig.2 BP network for predicting gas content

(2) Data samples preparation for learning

Take n gas content points measured on the spot and measure the burial depth of the basement, the thickness influence coefficient at the distance 50m to the roof, coal seam thickness, etc. at each gas content point and then create n learning samples.As the data samples have different dimensions, before input the BPNN, the data samples need normalizing.

(3) BPNN training

Set the model variables K_1, K_2, ..., K_p, the minimum mean square error, the learning rate, the momentum coefficient, the most times for training, and randomly initialize the weights and the thresholds of the network as a value from 0 to 1. Take the data samples after normalizing as the input of the network and start to learn until the minimum mean square error of the output of the network reaches the preset value (0.001). If the network can not converge or the training reaches the maximum times, it needs to adjust the learning rate or to reset the momentum coefficient and the most iterations until the network converges and meets the precision request.

(4) Forecasting

After training, the BPNN model is ensured. The data samples can be used as the forecasting samples and be input to the model and then give the forecasting results.

4. Forecasting results and analysis

4.1. Data selecting

According the above modeling steps, in this study, we use a three-layer BPNN to establish the gas content forecasting model for the coal mine. Take the number of the input layer nodes n=3, respectively representing the burial depth of the basement, the thickness influence coefficient at the distance 50m to the roof and the coal seam thickness. Take the number of the output layer l=1, representing the gas content. Take the number of the hidden layer nodes m=10. Create 45 learning samples according to the 45 gas content points measured on the spot and the relevant values of the burial depth of the basement (K_1), the thickness influence coefficient at the distance 50m to the roof (K_2), coal seam thickness (K_3), as Tab.1.

Tab.1 Learning sample basic data of gas content

Measure point	K_1（m）	K_2	K_3（m）	CH_4 measured value
1	120.1	0.934	2.4	4.95
2	624.19	1.133	7.6	11.6
3	437.9	1.32	5.89	6.52
4	731.9	1.067	9.7	10.83
5	226	0.792	3.2	5.1
6	476.8	0.368	7.94	9.75
7	461	0.891	4.9	6.89
8	226.7	1.086	1.9	6.08
9	462	0.945	2.9	10.96
10	309.4	1.45	5	7.65
11	291.9	0.3	4	7.9
12	150.2	1.1	6.2	8.3
13	180.3	0.45	6.5	5.46
14	372	0.98	6.41	8.11
15	278	0.85	5.28	5.36
16	625	1.46	9.2	14.13
17	392	0.6	4.8	6.55
18	581	1.51	4.1	10.27
19	392	1.23	5.6	7

20	325	1.13	3.46	8.97
21	232	0.76	5.17	7.70
22	272	1.03	5.2	8.83
23	178	0.46	2.5	3.21
24	231	0.52	3.2	4.64
25	352	0.96	2.86	7.76
26	380	1.17	3.45	9.92
27	374	1.06	3.5	7.48
28	386	0.99	3.78	7.96
29	374	1.1	4	8.21
30	132	1.23	4.1	6.9
31	221	1.18	5.1	8.53
32	232	1.21	5.97	7.89
33	246	1.18	3.62	6.54
34	346	1.2	4.32	6.86
35	391	0.91	4.8	9.68
36	142	0.36	2.32	2.45
37	182	0.45	3.2	3.42
38	200	0.51	5.6	3.38
39	221	0.63	5.72	4.23
40	256	0.79	6.37	6.46
41	227	0.62	6	5.13
42	138	0.52	4.36	3.34
43	176	0.47	2.6	2.9
44	200	0.65	2.52	5.98
45	302	0.85	4.2	5.5

4.2. Sample training

We use the software MATLAB to compile the program of the BPNN. Set the burial depth of the basement, the sandstone ratio at the 50m and the coal seam thickness as the model variables; set the minimum mean square error as 0.001, the learning rate as 0.3, the momentum coefficient as 0.8, the most times for training as 25000, and randomly initialize the weights and the thresholds of the network as a value from 0 to 1. Then, take the normalized data samples in Tab.1 as the input of the network and start to learn until the minimum mean square error of the output of the network reaches the preset value (0.001). If the network can not converge or the training reaches the maximum times 25000, it needs to adjust the learning rate or to reset the momentum coefficient and the most iterations until the network converges and meets the precision request.Forecasting result

According to the above training, the network takes 17065 times training by debugging and can meet the precision request. After training, we compare the forecasting result with that based on the traditional gas content forecasting model using multiple regression. The results are shown as Tab.2, Fig.3 and Fig.4.

Tab.2 Result contrast between neural network and multiple linear regression models

Measure point	CH_4 measured value	Forecasting value by BPNN	Residual error of BPNN	Multiple regression value	Residual error of Multiple regression
1	4.95	3.92	-1.03	3.54	-1.41
2	11.6	11.57	-0.03	11.55	-0.05
3	6.52	6.16	-0.36	8.65	2.13
4	10.83	10.77	-0.06	12.56	1.73
5	5.1	4.67	-0.43	4.89	-0.21
6	9.75	9.6	-0.15	8.93	-0.82
7	6.89	7.15	0.26	8.98	2.09
8	6.08	5.72	-0.36	5.98	-0.1
9	10.96	10.87	-0.09	9.62	-1.34
10	7.65	6.87	-0.78	7.17	-0.48
11	7.9	7.53	-0.37	6.95	-0.95
12	8.3	8.01	-0.29	5.81	-2.49
13	5.46	5.24	-0.22	5.71	0.25
14	8.11	7.89	-0.22	8.38	0.27
15	5.36	4.96	-0.4	5.75	0.39
16	14.13	14.06	-0.07	11.49	-2.64
17	6.55	6.25	-0.3	7.3	0.75
18	10.27	10.09	-0.18	10.94	0.67
19	7	7.61	0.61	8.13	1.13
20	8.97	8.81	-0.16	6.86	-2.11
21	7.7	6.97	-0.73	6.05	-1.65
22	8.83	8.38	-0.45	6.36	-2.47
23	3.21	3.47	0.26	4.43	1.22
24	4.64	4.74	0.1	5.21	0.57
25	7.76	7.62	-0.14	7.03	-0.73
26	9.92	8.92	-1	7.66	-2.26
27	7.48	7.62	0.14	7.82	0.34
28	7.96	9.19	1.23	7.79	-0.17
29	8.21	7.59	-0.62	8.13	-0.08
30	6.9	6.71	-0.19	6.05	-0.85
31	8.53	8.63	0.1	6.38	-2.15
32	7.89	7.75	-0.14	7.07	-0.82
33	6.54	6.27	-0.27	6.87	0.33
34	6.86	7.59	0.73	7.75	0.89
35	9.68	8.14	-1.54	8.11	-1.57
36	2.45	3.59	1.14	3.75	1.3

37	3.42	3.57	0.15	6.03	2.61
38	3.38	3.61	0.23	5.82	2.44
39	4.23	4.23	0	6.74	2.51
40	6.46	6.55	0.09	6.54	0.08
41	5.13	4.92	-0.21	6.51	1.38
42	3.34	3.28	-0.06	3.76	0.42
43	2.9	3.21	0.31	4.01	1.11
44	5.98	5.61	-0.37	4.54	-1.44
45	5.5	5.83	0.33	7.53	2.03

As shown in Fig.3 and Fig.4, the forecasting value using BPNN more accords with the measured value than that of the traditional gas content forecasting model using multiple regression. What is more, the fluctuation of the residual error of BPNN is smaller, which implies that the precision and feasibility of the BPNN forecasting are higher than the traditional multiple regression model. These results indicate that the BPNN model is appropriate for the analysis and forecasting of the coal seam gas content.

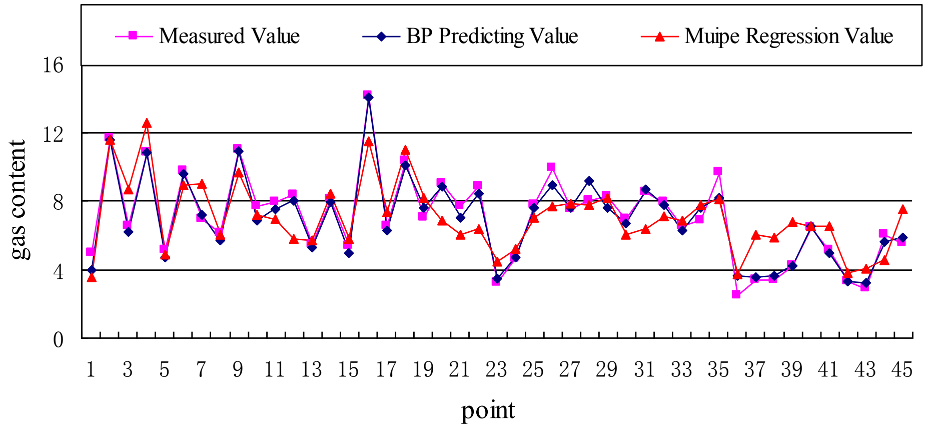

Fig.3 Comparison between the forecasting result and the measured value

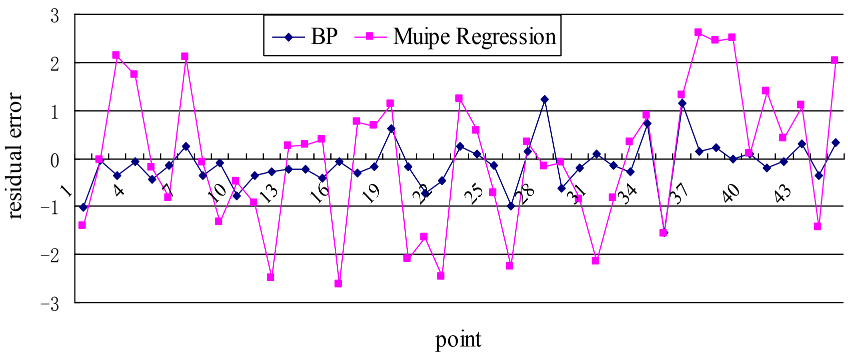

Fig.4 Comparison between the residual error of BPNN and that of multiple regression

5. Conclusions

(1) In this study, we analyze the basic theory of the BPNN and found the BPNN model of the gas content with the burial depth of the basement, the thickness influence coefficient at the distance 50m to the roof and the coal seam thickness.

(2) Combining the measured data on the spot with the BPNN, we get the forecasting result with the MATLAB program and compare the forecasting result with that obtained by traditional gas content forecasting model based on multiple regression. The analysis indicates that the precision and feasibility of the BPNN forecasting are higher than the traditional multiple regression model and the BPNN model is appropriate for the analysis and forecasting of the coal seam gas content.

(3) Due to the high precision and good real-time feature, using the BPNN theory to study the coal seam gas content can provide the theory basis for the coal and gas outburst prevention, which also has a good application prospect.

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